

# REPORT DOCUMENTATION PAGE

Form Approved  
OMB No. 0704-0188

Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden to Washington Headquarters Service, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington, DC 20503.

PLEASE DO NOT RETURN YOUR FORM TO THE ABOVE ADDRESS.

|   |             |                                 |                               |   |   |
|---|-------------|---------------------------------|-------------------------------|---|---|
| 1. REPORT DATE (DD-MM-YYYY)<br>07-03-2000   |             | 2. REPORT DATE<br>March 7, 2000 |                               | 3. DATES COVERED (From - To)<br>5/96 - 9/99       |   |
| 4. TITLE AND SUBTITLE<br><br>Neural Scene segmentation by oscillatory correlation   |             |                                 |                               | 5a. CONTRACT NUMBER                               |   |
|   |             |                                 |                               | 5b. GRANT NUMBER<br>N00014-96-1-0676              |   |
|   |             |                                 |                               | 5c. PROGRAM ELEMENT NUMBER                        |   |
| 6. AUTHOR(S)<br><br>DeLiang Wang  |             |                                 |                               | 5d. PROJECT NUMBER                                |   |
|   |             |                                 |                               | 5e. TASK NUMBER                                   |   |
|   |             |                                 |                               | 5f. WORK UNIT NUMBER                              |   |
| 7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)<br>The Ohio State University<br>1960 Kenny Road<br>Columbus, OH 43210-1016   |             |                                 |                               | 8. PERFORMING ORGANIZATION<br>REPORT NUMBER       |   |
| 9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)<br>Office of Naval Research<br>800 North Quincy Street<br>Ballston Tower One<br>Arlington, VA 22217   |             |                                 |                               | 10. SPONSOR/MONITOR'S ACRONYM(S)<br>ONR           |   |
|   |             |                                 |                               | 11. SPONSORING/MONITORING<br>AGENCY REPORT NUMBER |   |
| 12. DISTRIBUTION AVAILABILITY STATEMENT<br>APPROVED FOR PUBLIC RELEASE  |             |                                 |                               |   |   |
| 13. SUPPLEMENTARY NOTES   |             |                                 |                               |   |   |
| 14. ABSTRACT<br>The segmentation of a visual scene into a set of coherent patterns (objects) is a fundamental aspect of perception, which underlies a variety of important tasks such as figure/ground segregation, and scene analysis. An innovative approach has been developed that uses neural oscillator networks to segment images. The framework, called oscillatory correlation, encodes the binding of pixels by phases of neural oscillators, resulting in a dynamical systems approach. The approach has been evaluated by computer simulations using both synthetic and real imagery, including intensity, range, motion, texture images. The results have been very competitive. |             |                                 |                               |   |   |
| 15. SUBJECT TERMS<br><br>scene segmentation, neural oscillators, oscillatory correlation, image analysis  |             |                                 |                               |   |   |
| 16. SECURITY CLASSIFICATION OF:   |             |                                 | 17. LIMITATION OF<br>ABSTRACT | 18. NUMBER<br>OF PAGES                            | 19a. NAME OF RESPONSIBLE PERSON           |
| a. REPORT   | b. ABSTRACT | c. THIS PAGE                    |                               |   | 19b. TELEPHONE NUMBER (Include area code) |

# Final ONR Project Report

DeLiang Wang

*Department of Computer and Information Science  
and Center for Cognitive Science  
The Ohio State University*

March, 2000

## 1. INTRODUCTION

The project, entitled "Neural Scene Segmentation By Oscillatory Correlation" (N00014-96-1-0676), was awarded as a three-year YIP grant in May 1996, and it ended in September 1999. The total project budget was \$330,501. The goal of the project was to develop the oscillatory correlation approach for image segmentation, whereby the binding of pixels is encoded by phases of neural oscillators. This project was very productive, and led to major accomplishments.

In this final project report, I summarize the progress made during this project. Section 2 provides an overview of scientific progress, and Section 3 gives more description of some major accomplishments. Section 4 provides a list of scientific publications resulting from the grant, and these publications contain full details of the progress. Finally, Section 5 provides a list of Ph.D. dissertations resulting from this grant.

## 2. OVERVIEW OF SCIENTIFIC PROGRESS

Prior to this project, our work on the oscillatory correlation approach resulted in general LEGION architecture for scene segmentation. LEGION stands for Locally Excitatory Globally Inhibitory Oscillator Networks, and builds on relaxation oscillators. With the introduction of a lateral potential to each oscillator, a solution to remove noisy regions in a scene was proposed for LEGION so that it suppresses the oscillators corresponding to noisy and insignificant regions, without affecting those corresponding to significant ones. We have analytically shown that the resulting oscillator network separates a scene into several major regions, plus a background consisting of all noisy ones. We have found a fast numerical method - the singular limit method - for integrating relaxation oscillator networks, and obtained extensive results on analyzing time complexity of computing using oscillatory correlation. Also, we have found that relaxation oscillators show a wide spectrum of behavior with parameter adjustment, ranging from integrate-

20000320 043

and-fire oscillators to sinusoidal oscillators, and LEGION architecture can be extended to integrate-and-fire oscillators. Recently, on the basis of oscillatory correlation, we have solved the long-standing Minsky-Papert connectedness problem, which is the problem of detecting whether an arbitrary figure is connected by a neural network.

Although the above progress is largely on theoretical aspects of oscillatory dynamics, the thrust of the work conducted during this project was to apply the oscillatory correlation approach to image segmentation. The types of imagery we have successfully dealt with are gray-level medical and aerial images, range (depth) images, texture images, and motion images (image sequences). On medical images, we have obtained excellent results in segmenting anatomical structures of the brain from CT and MRI imagery. On aerial images, we have proposed a new methodology that combines neural network learning for seed selection, weight adaptation for noise removal and oscillatory correlation. The resulting method has been applied to segmentation and object extraction from large-scale aerial imager, and extensive comparisons show that our results are significantly better than those obtained by other methods. On range image segmentation, we have proposed a method for local range detection that combines depth, surface normal, and mean and Gaussian curvatures. On texture images, we have proposed to use Gaussian Markov Random Fields as an effective way of texture feature extraction, and applied the singular limit method for integrating a large system of differential equations. The resulting system has been tested on texture images, and has been favorably compared with other algorithmic systems for texture image segmentation. On motion-based segmentation, our methodology integrates motion and brightness for analyzing image sequences, and a subsequent network combines the two analyses to refine local motion estimates. Again, the resulting system has been successfully evaluated with real image sequences, and compared with other algorithms for motion analysis and segmentation.

Additionally, we have proposed a new architecture for object selection - the task of selecting target objects in scenes. Our selection network builds on LEGION dynamics and slow inhibition, and has been applied to select the most salient object in gray-level images. Very recently, we have completed a study that integrates a primitive segmentation stage with a model of associative memory. The integrated system is evaluated with a systematic set of 3-D line drawing objects, and memory-based organization is responsible for a large improvement in performance.

### **3. DESCRIPTION OF SELECTED WORKS**

#### **3.1 Synchronization and Desynchronization in Large Oscillator Networks**

A long-standing problem in neural computation has been the problem of connectedness, first identified by Minsky and Papert in their 1969 landmark book on perceptrons, which is the problem

of detecting whether an arbitrary figure is connected by a neural network. This problem served as the cornerstone for them to analytically establish that perceptrons are fundamentally limited in computing geometrical (topological) properties. Despite the breakthrough made in training multilayer networks in the mid-eighties, which led to a remarkable resurgence in neural network research, the Minsky-Papert problem remained unsolved as stated in their expanded 1988 edition of the 1969 book. We have recently solved this problem by employing a different class of neural networks - oscillator networks. To solve the problem, the representation of oscillatory correlation is employed, and it emerges from a LEGION network. It is further shown that these oscillator networks exhibit sensitivity to topological structure, which may lay a neurocomputational foundation for explaining the psychophysical phenomenon of topological perception.

Our solution is published a few weeks ago in *Neural Computation* (Wang, 2000; see journal publications listed in Sect. 4). Figure 1 illustrates our solution by showing the response of a 30x30 LEGION network to two figures: one connected and one disconnected. The connected figure is a "cup" shown in Fig. 1A, while the disconnected one is the image of the word "CUP" shown in Fig. 1B. The LEGION network is solved using a Runge-Kutta method. The oscillators of the network start with random phases. Fig. 1C displays temporal activity of all the stimulated oscillators for the connected cup image. Unstimulated oscillators are omitted from the display because they do not oscillate. The oscillators corresponding to each pattern are combined in the display, and thus appear like a single oscillator when they are in synchrony. The upper panel shows the oscillator block corresponding to the cup, and the middle panel shows the activity of the global inhibitor. Synchrony occurs in the first cycle of oscillations. The case for the disconnected "CUP" is shown in Fig. 1D. The upper three traces in Fig. 1D show the three blocks corresponding to the three patterns, respectively, and the fourth one the activity of the global inhibitor. The bottom traces in both Fig. 1C and Fig. 1D show the response of a connectedness predicate for these two cases, where  $\theta$  is a threshold. Beyond a short beginning duration corresponding to the process of synchronization and desynchronization, the predicate correctly reveals connectedness.

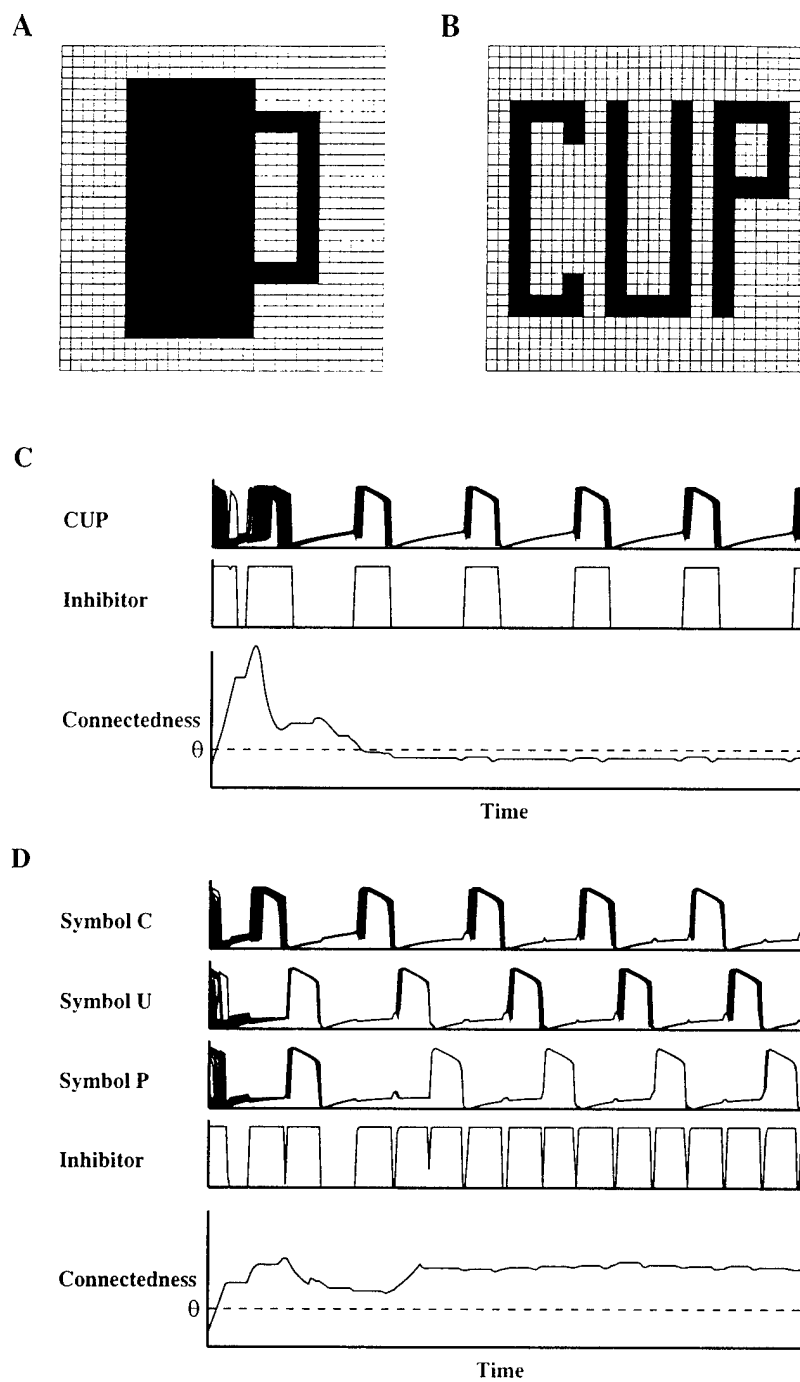


Figure 1

### 3.2. Medical Image Segmentation

Advances in visualization technology and specialized graphic workstations allow clinicians to virtually interact with anatomical structures contained within sampled medical image datasets. A hindrance to the effective use of this technology is the difficult problem of image segmentation. We have studied LEGION networks for grouping similar features and segregating dissimilar ones in medical imagery. We have extracted an algorithm from LEGION dynamics and proposed an adaptive scheme for grouping, and applied the algorithm to 2D and 3D (volume) CT and MRI medical image datasets. In addition, we have compared our algorithm with other algorithms, including active contours, learning vector quantization, and Markov/Gibbs random field models, for medical image segmentation, as well as with manual segmentation. The comparisons suggest that LEGION is an effective computational framework to tackle the problem of medical image segmentation.

The results are published in *IEEE Trans. on Medical Imaging* (Shareef, Wang, and Yagel, 1999). Figure 2 illustrates the performance of our system. Top left shows a 2D MRI image. Top right gives a color map showing the result of segmenting the image by a LEGION network. Different segments are indicated by different colors. All of the major anatomical regions are correctly segmented. The rest of the figure shows the segmentation of a 3D MRI volume dataset for extracting the brain. The segmentation results are displayed using volume rendering. The middle row shows the results of a top view (the front facing downward) and the bottom row shows a side view (the front facing leftward), respectively. The two left images show the results of our system, and the two right ones show the corresponding results produced by slice-by-slice manual segmentation. Although the results of manual segmentation fit well with the stereotype of our anatomical knowledge, the results of our algorithm actually better reflect details of this dataset.

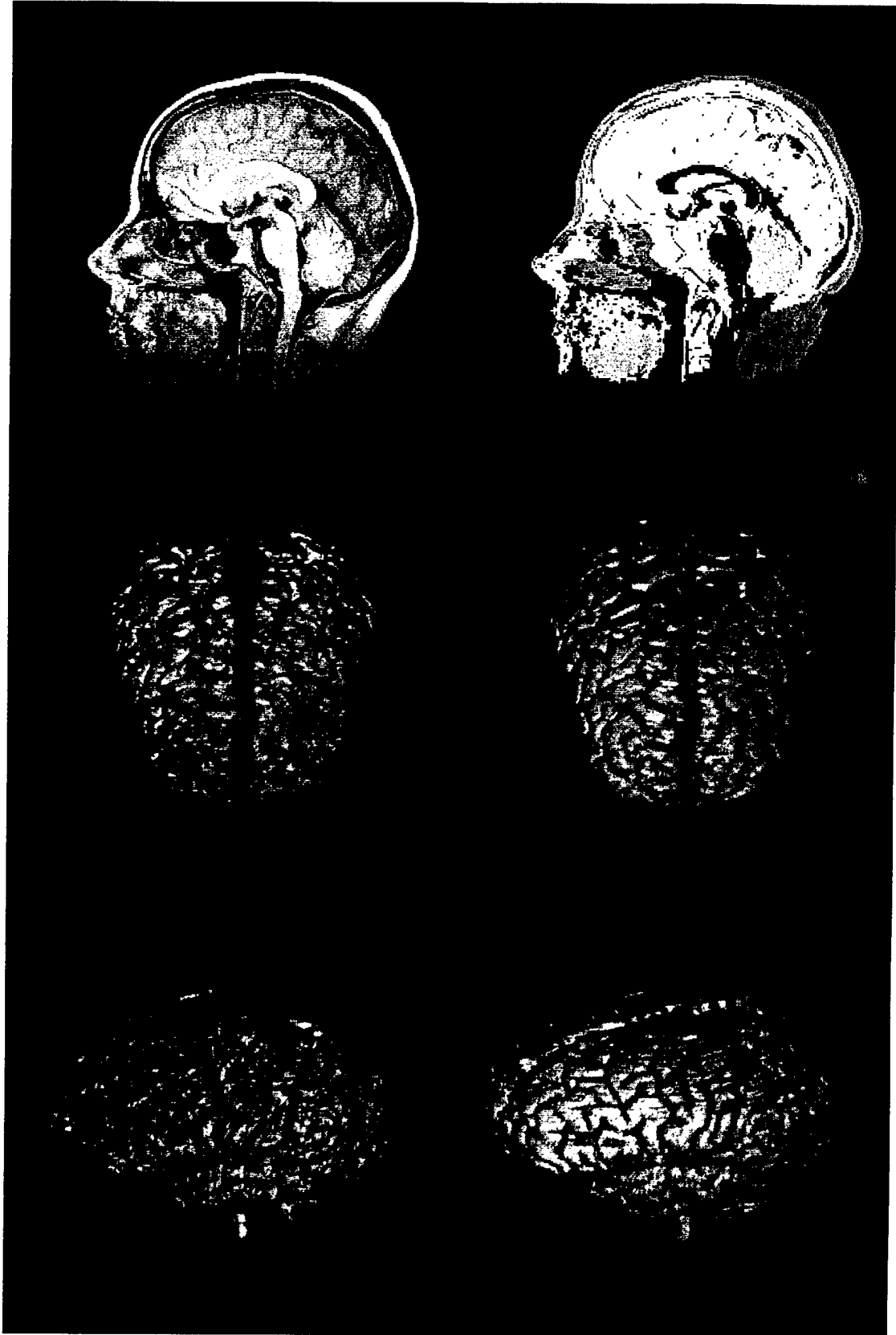


Figure 2

### 3.3 Aerial Image Analysis

To deal with aerial image segmentation and object extraction, we have proposed a weight adaptation method during segmentation, which plays the roles of noise removal and feature extraction. In particular, our weight adaptation scheme is insensitive to termination times - a common problem in various smoothing techniques in image processing - and the resulting dynamic weights in a wide range of iterations are applicable to achieve the same segmentation results. The resulting segmentation method combines weight adaptation and oscillatory correlation. For a variety of large-scale aerial images provided by the U.S. Geological Survey (USGS) through the Ohio State University Center for Mapping, our algorithm achieves very good segmentation results and yields favorable comparisons with other recent image processing algorithms, including nonlinear smoothing and multi-scale segmentation.

The results are summarized in two papers to appear in *IEEE Trans. on Neural Networks* (Chen, Wang, and Liu, 2000) and *IEEE Trans. on GeoScience and Remote Sensing* (Liu, Chen, and Wang, 2000), respectively. Figure 3 illustrates the results of extracting hydrographic objects from two satellite images. The original images containing water bodies are shown in the top row. The middle row shows the corresponding extraction results. To facilitate comparisons, we display the water bodies by marking them as white and superimposing them on the original images. The bottom row provides the corresponding USGS 1:24,000 topographic maps. Our algorithm extracts the water bodies precisely, even along narrow river branches. Moreover, important details are preserved, such as the small island near the uppermost river branch in the upper left image. A careful comparison between the extracted regions and the maps indicate that the former portray the images even a little better, because stationary maps do not reflect well the changing nature of geography.

Figure 4A shows a very large image (6204x7676) from the Washington East, D.C.-Maryland area. Figure 4B shows the result of hydrographic object (river in this case) extraction by our system. For comparison, Figure 4C shows the corresponding result by a multilayer perceptron. The perceptron is first trained using typical samples from both hydrographic and non-hydrographic regions, and is then applied to classify the entire image. It is clear from Figure 4 that our system performs large-scale hydrographic extraction with high accuracy, and does a much better job than classification by a multilayer perceptron.



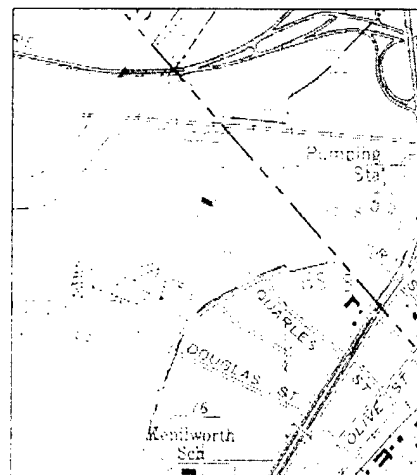
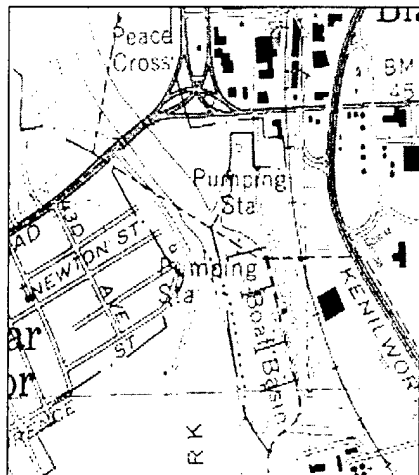
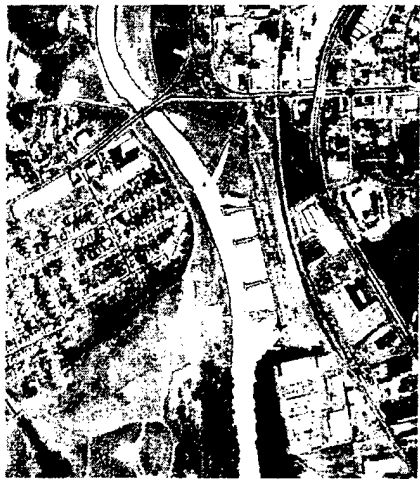


Figure 3

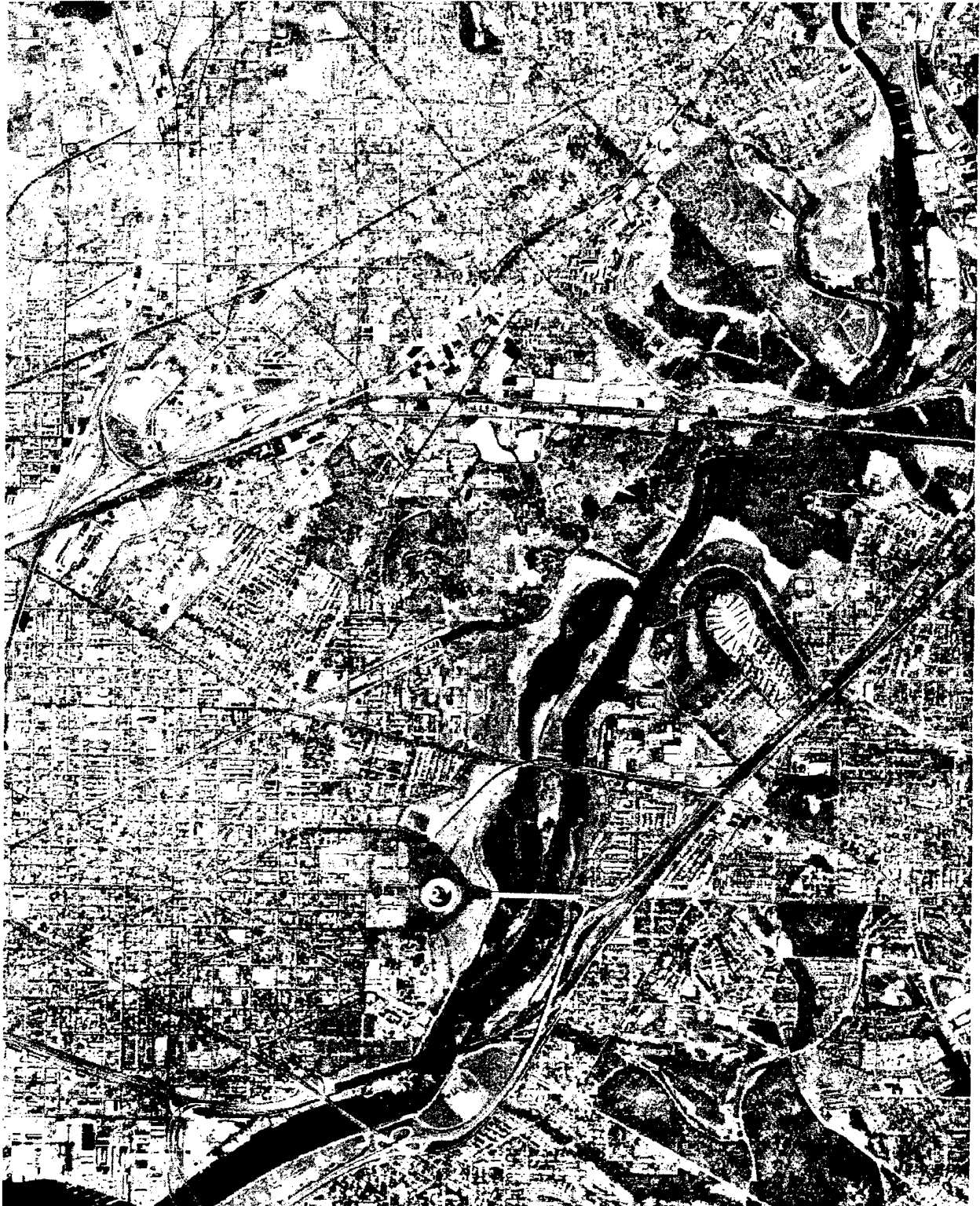


Figure 4A



Figure 4B

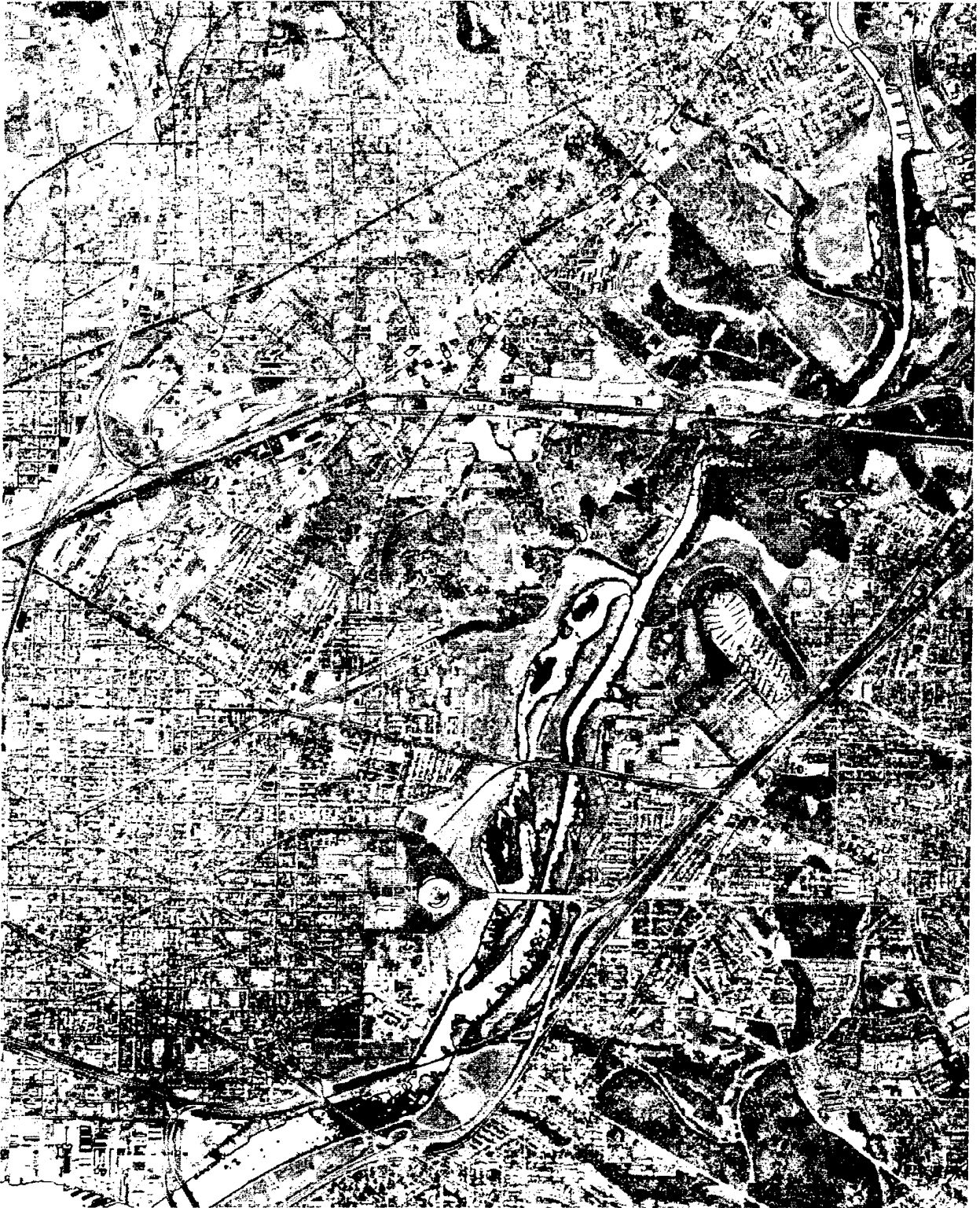


Figure 4C

### 3.4 Texture segmentation

Texture is important for visual analysis. Segmentation based on texture, however, has proven to be a very difficult task in machine vision. Many methods have been proposed to deal with the problem, including statistical, geometrical, and model-based methods. Our proposed method consists of two parts. The first part determines a set of texture features with a novel method inspired by Gaussian Markov Random Fields (GMRF). Unlike other GMRF-based methods, ours is a generic formulation, not limited by a fixed set of texture types. The second part is a two-dimensional LEGION network. The coupling strengths between neighboring oscillators are determined by texture feature differences. In our simulations, a large system of differential equations is solved using the singular limit method. A careful comparison with other methods shows that our results are at least as good as those commonly used in computer vision. Also, our approach offers several methodological advantages: the assumptions embedded in our method are weaker than other methods (MRF for example) and our method tends to work satisfactorily for novel texture types.

As an illustration, Figure 5 shows some of our segmentation results. The left side displays five original images taken from the commonly used Brodatz Album. The right side shows the corresponding results of LEGION segmentation, where different gray levels indicate different segments and black scattered areas indicate the background resulting from LEGION segmentation.

Given a distinct texture (a giraffe in this example), a target can be effectively extracted from a cluttered scene. This task of target extraction based on natural texture is illustrated in Figure 6. The top is an input image that contains a giraffe and the bottom is the result of our texture target extraction. The extracted target is embedded in the original by lowering the intensity of those pixels that do not belong to the target.

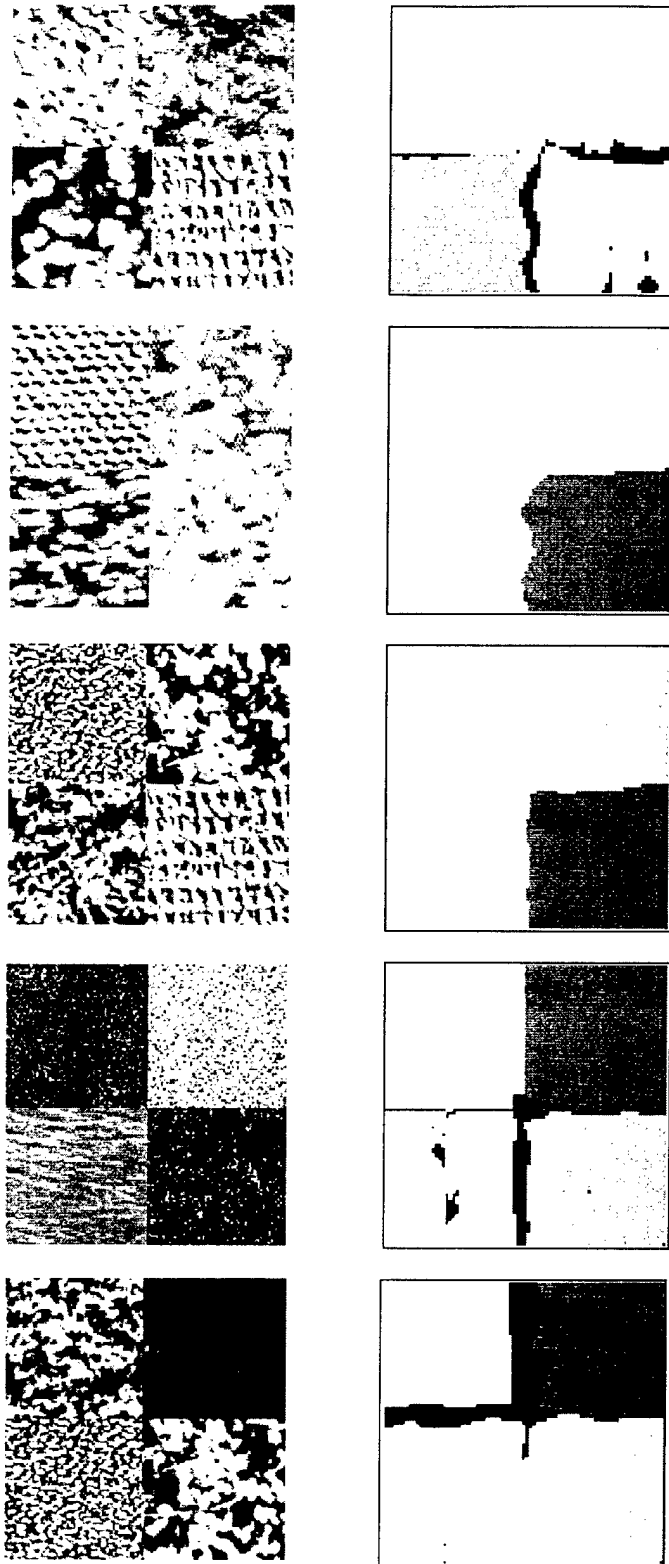


Figure 5

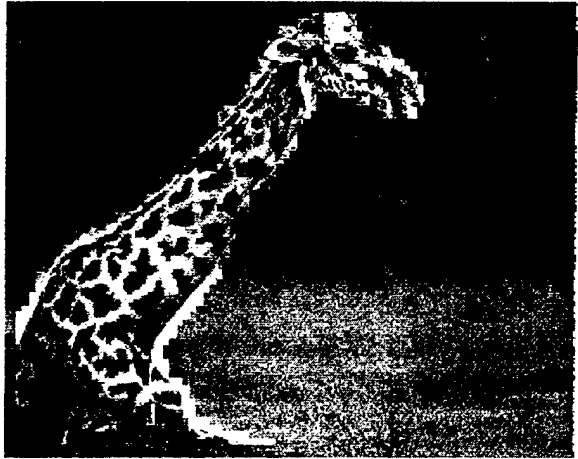


Figure 6



### 3.5 Motion segmentation

This part of the project concerns analysis and segmentation of images based on motion. Unlike many algorithms for motion-based segmentation, our system integrates motion and brightness for analyzing image sequences. We have proposed two parallel pathways that first process motion and brightness separately, and then a subsequent network combines the two to refine local motion estimates. Like other segmentation tasks we have dealt with, LEGION networks are employed for final grouping and segmentation. In addition to successful evaluation with real image sequences, our system exhibits a number of important properties in human motion perception; these include motion transparency and an elegant treatment of the so-called blank wall problem, which refers to our ability to perceive a moving whole despite no local motion signal in the interior of the whole.

The results are summarized in a paper to appear in *IEEE Trans. on Neural Networks* (Cesmeli and Wang, 2000). Figure 7 illustrates the performance of our method on real moving scenes. Fig. 7A shows one frame of the input sequence, where a motorcycle rider jumps to a (dry) canal with his motorcycle while the camera is tracking him. Due to the camera motion, the rider and his motorcycle have a downward motion with a small rightward component and the image background has an upright diagonal motion. Fig. 7B shows motion estimates after integrating motion and brightness analyses, and our estimated optic flow is largely correct. Based on these estimates, the rider with his motorcycle is accurately segmented from the image background as depicted in Figure 7C. As in the segment of the rider and his motorcycle, regions with different texture and brightness are grouped into a single segment due to common motion.

We have compared our neural oscillator model with three representative algorithms proposed by Horn and Schunck (1981), Anandan (1987), and Black (1996), respectively, for the scene given in Figure 7A. The results of the algorithms of Horn and Schunck, Anandan, and Black are given in Figure 7D, E, and F, respectively. The Horn and Schunck algorithm cannot capture the motion of the regions (Fig. 7D), and similarly, the Anandan algorithm cannot accurately localize the motion boundaries (Fig. 7E). The Black algorithm offers the best result by far among the three (Fig. 7F). Unlike ours, the Black algorithm requires the number of regions as an input parameter. When two regions are assumed in this case, it can group the locations into two segments that best account for the motion distribution in the scene. However, local motions are not estimated accurately and the motion boundary between the rider/motorcycle segment and the image background is not well localized. Except for the limitation that our model does not produce motion estimates near the image border (see Fig. 7B), our neural network method yields the most accurate motion boundaries.



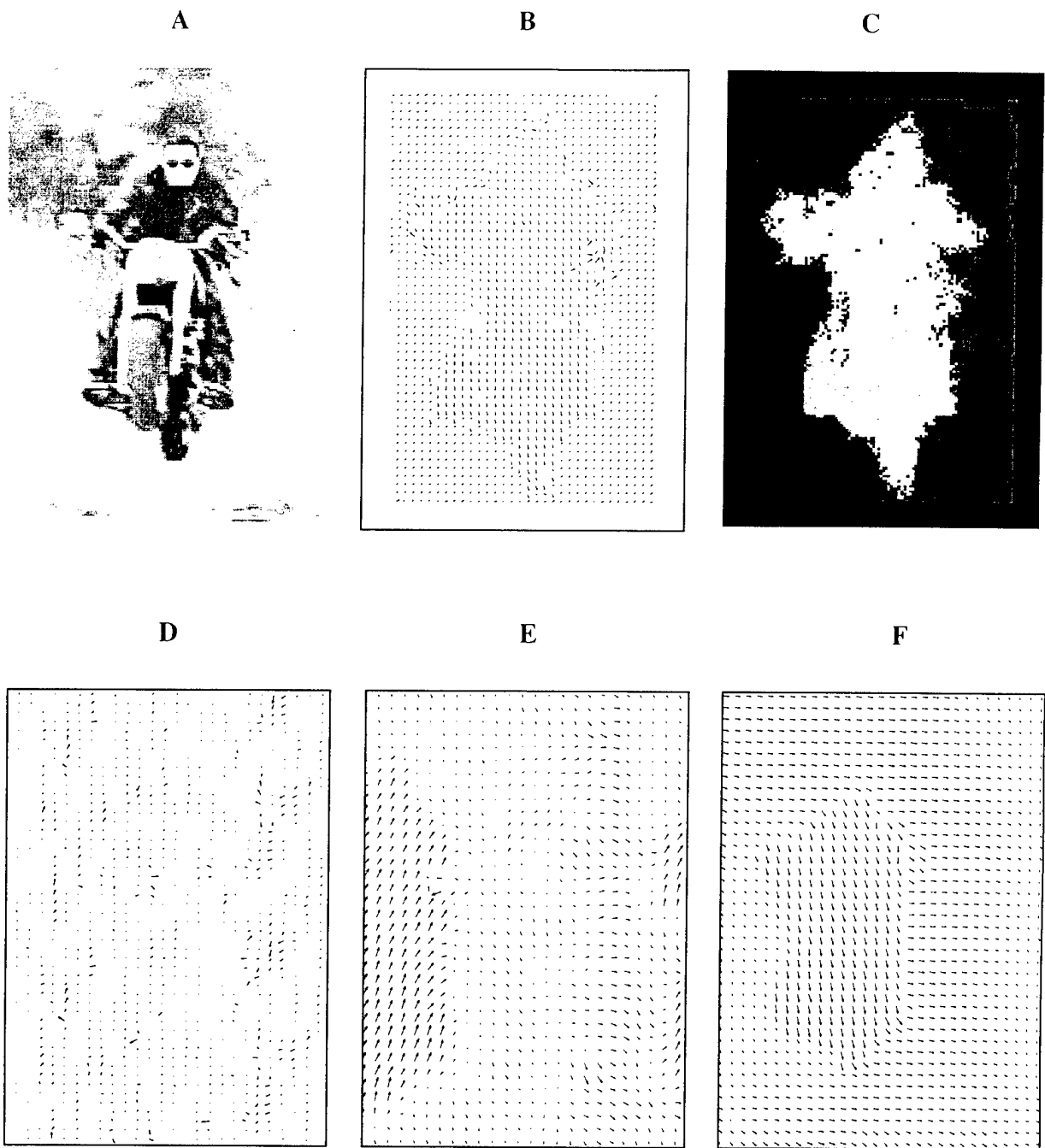


Figure 7

## 4. PUBLICATION LIST

### 4.1 Journal Publications

- J1. Wang D.L. and Terman D. (1997): Image segmentation based on oscillatory correlation. *Neural Computation*, vol. 9, 805-836 (For errata see *Neural Computation*, vol. 9, 1623-1626, 1997).
- J2. Brown G.J. and Wang D.L. (1997): Modelling the perceptual segregation of double vowels with a network of neural oscillators. *Neural Networks*, vol. 10, 1547-1558.
- J3. Wang D.L. (1997): On the computational basis of synchronized codes. *Behavioral and Brain Sciences*, vol. 20, 700-701.
- J4. Campbell S.R. and Wang D.L. (1998): Relaxation oscillators with time delay coupling. *Physica D*, vol. 111, 151-178.
- J5. Linsay P.S. and Wang D.L. (1998): Fast numerical integration of relaxation oscillator networks based on singular limit solutions. *IEEE Transactions on Neural Networks*, vol. 9, 523-532.
- J6. Shareef N., Wang D.L., and Yagel R. (1999): Segmentation of medical images using LEGION. *IEEE Transactions on Medical Imaging*, vol. 18, 74-91.
- J7. Liu X. and Wang D.L. (1999): Range image segmentation using a relaxation oscillator network. *IEEE Transactions on Neural Networks*, vol. 10, 564-573.
- J8. Wang D.L. and Brown G.J. (1999): Separation of speech from interfering sounds based on oscillatory correlation. *IEEE Transactions on Neural Networks*, vol. 10, 684-697.
- J9. Wang D.L. (1999): Object selection based on oscillatory correlation. *Neural Networks*, vol. 12, 579-592.
- J10. Campbell S.R., Wang D.L., and Jayaprakash C. (1999). Synchrony and desynchrony in integrate-and-fire oscillators. *Neural Computation*, vol. 11, 1595-1619.
- J11. Liu X., Wang D.L., and Ramirez J.R. (2000). Boundary detection by contextual nonlinear smoothing. *Pattern Recognition*, vol. 33, pp. 263-280.
- J12. Wang D.L. (2000): On connectedness: a solution based on oscillatory correlation. *Neural Computation*, vol. 12, pp. 131-139.
- J13. Chen K., Wang D.L., and Liu X. (2000): Weight adaptation and oscillatory correlation for image segmentation. *IEEE Transactions on Neural Networks*, in press.
- J14. Cesmeli E. and Wang D.L. (2000): Motion Segmentation Based on Motion/Brightness Integration and Oscillatory Correlation. *IEEE Transactions on Neural Networks*, in press.
- J15. Liu X., Chen K., and Wang D.L. (2000): Extraction of Hydrographic Regions from Remote Sensing Images Using an Oscillator with Weight Adaptation. *IEEE Transactions on GeoScience and Remote Sensing*, to appear.

## 4.2 Book Chapters

- B1. Wang D.L. (1998): Stream segregation based on oscillatory correlation. In Rosenthal D. and Okuno H.G. (eds.), *Computational Auditory Scene Analysis*, pp. 71-86, Lawrence Erlbaum, Mahwah NJ.
- B2. Wang D.L. (1999): Relaxation oscillators and networks. In Webster J. (ed.), *Encyclopedia of Electrical and Electronics Engineering*, Wiley & Sons, vol. 18, pp. 396-405.
- B3. Brown G.J. and Wang D.L. (2000): Timing is of the essence: Neural oscillator models of auditory grouping. In Greenberg S. and Ainsworth W. (ed.), *Listening to Speech: An Auditory Perspective*, Oxford University Press, in press.

## 4.3 Conference Papers

- C1. Wang D.L. and Terman D. (1996): Image segmentation by neural oscillator networks. *Proceedings of the IEEE International Conference on Neural Networks (ICNN-96)*, pp. 1534-1539.
- C2. Campbell S. and Wang D.L. (1996): Loose synchrony in relaxation oscillator networks with time delays. *Proceedings of ICNN-96*, pp. 828-833.
- C3. Wang D.L. and Yuwono B. (1996): A neural model of sequential memory. *Proceedings of ICNN-96*, pp. 834-839.
- C4. Campbell S. and Wang D.L. (1996): Loose synchrony in networks of relaxation oscillators with time delays. *Proceedings of World Congress on Neural Networks (WCNN-96)*, pp. 717-720.
- C5. Shareef N., Wang D.L., and Yagel R. (1996): Segmentation of medical data using locally excitatory globally inhibitory oscillator networks. *Proceedings of WCNN-96*, pp. 1245-1248.
- C6. Wang D.L. and Yuwono B. (1996): Incremental learning of complex temporal patterns. *Proceedings of WCNN-96*, pp. 757-762.
- C7. Brown G.J. and Wang D.L. (1997): Modelling the perceptual separation of concurrent vowels with a network of neural oscillators. *Proceedings of ICNN-97*, pp. 569-574.
- C8. Campbell S. and Wang D.L. (1997): Relaxation oscillator networks with time delays. *Proceedings of ICNN-97*, pp. 645-650.
- C9. Cesmeli E. and Wang D.L. (1997): Texture segmentation using Gaussian Markov random fields and LEGION. *Proceedings of ICNN-97*, pp. 1529-1534.
- C10. Liu X.W. and Wang D.L. (1997): Range image segmentation using an oscillatory network. *Proceedings of ICNN-97*, pp. 1656-1660.
- C11. Wang D.L. (1997): Object selection by a neural oscillator network. *Proceedings of International Conference on Neural Information Processing*, pp. 1137-1140.

- C12. van der Kouwe A.J.W. and Wang D.L. (1997): Temporal alignment, spatial spread and the linear independence criterion for blind separation of voices. *Proceedings of IEEE EMBS*, pp. 1994-1996.
- C13. Wang D.L. (1998): Object selection by oscillatory correlation. *Proceedings of International Joint Conference on Neural Networks (IJCNN-98)*, pp. 1182-1187.
- C14. Campbell S. and Wang D.L. (1998): Synchrony and desynchrony in integrate and fire oscillators. *Proceedings of IJCNN-98*, pp. 1498-1503.
- C15. Liu X.W., Wang D.L., and Ramirez J.R. (1998): Extracting hydrographic objects from satellite images using a two-layer neural network. *Proceedings of IJCNN-98*, pp. 897-902.
- C16. Chen K. and Wang D.L. (1998): Perceiving spirals and inside/outside relations by a neural oscillator network. *Proceedings of IJCNN-98*, pp.619-624.
- C17. Cesmeli E., Wang D.L., Lindsey D.L., and Todd J.T. (1998): Motion segmentation using temporal block matching and LEGION. *Proceedings of IJCNN-98*, 2069-2074.
- C18. Liu X., Wang D.L., and Ramirez J R. (1998): A two-layer neural network for robust image segmentation and its application in revising hydrographic features. *International Archives of Photogrammetry and Remote Sensing*, vol. 32, part 3/1, pp. 464-472.
- C19. Liu X., Wang D.L., and Ramirez J.R. (1998): Oriented statistical nonlinear smoothing filter. *Proceedings of the International Conference on Image Processing*, vol. 2, pp. 848-852.
- C20. Cesmeli E. and Wang D.L. (1998), "Gauss Markov Rasgele Alanlari ve Salingan Sinir Aglariyla Doku Bolutlemesi," SIU-98, Ankara TURKEY (in Turkish).
- C21. Chen K. and Wang D.L. (1999): Perceiving without learning: from spirals to inside/outside relations. *Advances in Neural Information Processing Systems 11 (NIPS-98)*, MIT Press, pp. 10-16.
- C22. Liu X. and Wang D.L. (1999): A figure-ground segregation network for perceptual organization. *Proceedings of IJCNN-99*, 6 pages on CD-ROM.
- C23. Liu X. and Wang D.L. (1999): Amodal completion using a figure-ground segregation network and local diffusion. *Proceedings of IJCNN-99*, 6 pages on CD-ROM.
- C24. Cesmeli E. and Wang D.L. (1999): Motion segmentation based on motion/brightness integration and oscillatory correlation. *Proceedings of IJCNN-99*, 6 pages on CD-ROM.
- C25. Brown G.J. and Wang D.L. (1999): The separation of speech from interfering sounds: an oscillatory correlation approach. *Proceedings of IJCNN-99*, 6 pages on CD-ROM.
- C26. Chen K. and Wang D.L. (1999): Image segmentation based on a dynamically coupled neural oscillator network. *Proceedings of IJCNN-99*, 6 pages on CD-ROM.
- C27. Brown G.J. and Wang D.L. (1999): An oscillatory correlation framework for computational auditory scene analysis. *Proceedings of NIPS-99*, in press.
- C28. Liu X. and Wang D.L. (1999): Perceptual organization based on temporal dynamics. *Proceedings of NIPS-99*, in press.

## 5. RESULTING PH.D. DISSERTATIONS

Name. Dissertation title. Date completed

Shannon R. Campbell, "Synchrony and desynchrony in neural oscillators," Summer 1997.

Soowon Kim, "Computational architecture for the detection and segmentation of coherent motion," Summer 1997.

Erdogan Casmeli, "Texture-and motion-based image segmentation using oscillatory correlation," Spring 1999.

Xiuwen Liu, "Computational investigation of feature extraction and image organization," Autumn 1999.